NEW PARAMETER REDUCTION OF SOFT SETS

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ABSTRACT

Several algorithms exist to address the issues concerning parameter reduction of soft sets. The most recent concept of Normal Parameter Reduction (NPR) is introduced, which overcomes the problem of suboptimal choice and added parameter set of soft sets. However, the algorithm involves a great amount of computation. In this thesis, a New Efficient Normal Parameter Reduction algorithm (NENPR) of soft sets is proposed based on the new theorems, which have been proved and presented. The proposed technique can be carried out without parameter important degree and decision partition. As a result, it can involve relatively less computation, compared with the algorithm of NPR. The experimental results are analyzed and comparisons are done with three real-life datasets and ten synthetic generated datasets. The computational complexity is described in terms of the number of entry access, the number of parameter importance degree access and oriented-parameter access, and the number of candidate parameter reduction set. From these experimental results, some conclusions can be drawn that NENPR improves the number of entry access, the number of parameter importance degree access and oriented-parameter access, the number of candidate parameter reduction set and the executing time of NPR averagely up to 95.21%, 52.45%, 53.58% and 60.02% through three real-life datasets and ten synthetic generated datasets, respectively. Sum up, NENPR provides the better solutions for capturing the normal parameter reduction compared with NPR. An interval-valued fuzzy soft set is a special case of a soft set by combining the interval-valued fuzzy set and soft set. However, up to the present, the previous work has not involved parameter reduction of the interval-valued fuzzy soft sets. In this thesis, four new parameter reductions of the interval-valued fuzzy soft sets are proposed: Optimal Choice Considered Parameter Reduction (OCCPR), Invariable Rank of Decision Choice Considered Parameter Reduction (IRDCCPR), Standard Parameter Reduction (SPR) and Approximate Standard Parameter Reduction (ASPR). The related heuristic algorithms are given. In order to show the high efficiency of the proposed four algorithms, comparisons and analysis for decision making between OCCPR, IRDCCPR, ASPR, SPR and directly Interval-Valued Fuzzy Soft Sets based Fuzzy Decision Making algorithm (IVFSS-FDM) with three real-life datasets and ten synthetic generated datasets are made. Average percent of improvement of four proposed algorithms compared with IVFSS-FDM on the executing time concerning all of datasets are 80.28%, 56.37%, 47.44%, 10%, respectively. From these experimental results, conclusions can be drawn that our four proposed algorithms have much higher efficiency compared with directly IVFSS-FDM for decision making and four approaches have the respective merits and demerits. Therefore these proposed methods can be applied into the different situations.

ABSTRAK

Beberapa algoritma wujud untuk menangani isu-isu berkaitan dengan pengurangan parameter set lembut. Konsep yang paling terkini Pengurangan Parameter Normal (NPR) telah diperkenalkan, yang mengatasi masalah pilihan suboptimal dan menambah parameter yang ditetapkan set lembut. Walau bagaimanapun, algoritma tersebut sukar untuk difahami dan melibatkan jumlah pengiraan yang besar. Dalam tesis ini, algoritma Pengurangan Parameter Biasa Cekap yang Baru (NENPR) untuk set lembut dicadangkan berdasarkan teorem yang baru, yang telah dibuktikan dan dibentangkan. Teknik yang dicadangkan boleh dijalankan tanpa darjah parameter penting dan pembahagian keputusan. Akibatnya, ia boleh melibatkan pengiraan yang kurang dan lebih mudah untuk difahami dan dilaksanakan, berbanding dengan algoritma pengurangan parameter normal. Keputusan eksperimen dianalisis dan perbandingan dilakukan dengan sepuluh set data Boolean. Kerumitan pengiraan diterangkan dari segi bilangan akses masuk, bilangan parameter akses darjah kepentingan dan akses berorientasikan parameter, serta bilangan calon yang ditetapkan pengurangan parameter. Daripada keputusan ujikaji ini, beberapa kesimpulan boleh dinyatakan bahawa NENPR meningkatkan bilangan akses masuk, bilangan parameter akses darjah kepentingan dan akses berorientasikan-parameter, serta bilangan calon set parameter dan pengurangan masa pelaksanakan daripada NPR purata sehingga 95.21%, 52.45%, 53.58% dan 60.02% melalui tiga set data sebenar dan 10 set data sintetik yang dijana, masing-masing. Ringkasnya, NENPR menyediakan penyelesaian yang lebih baik untuk mendapat pengurangan parameter normal berbanding kepada NPR. Suatu selang-penting set kabur yang lembut ialah kes khas set yang lembut dengan menggabungkan nilai selang set kabur dan set lembut. Walau bagaimanapun, sehingga kini, kerja-kerja yang sebelumnya tidak melibatkan pengurangan parameter selang penting set kabur yang lembut. Dalam tesis ini, empat parameter pengurangan baru selang penting set kabur yang lembut dicadangkan: Pilihan Parameter Optimum yang Dipertimbangkan Pengurangan (OCCPR), Peringkat Tetap Pilihan Keputusan Dipertimbangkan Pengurangan Parameter (IRDCCPR), Pengurangan Parameter Standard (SPR) dan Anggaran Parameter Standard Pengurangan (ASPR). Algoritma heuristik berkaitan diberi. Dalam usaha untuk terus menjelaskan empat kaedah yang dicadangkan, perbandingan dan analisis telah dibuat antara selepas OCCPR, IRDCCPR, ASPR, SPR dan IVFSS-FDM dengan tiga set data sebenar dan 10 set data sintetik yang dijana. Peratus purata peningkatan empat algoritma yang dicadangkan berbanding dengan IVFSS-FDM adalah 80.28%, 56.37%, 47.44%, dan 10% masing-masing. Kesimpulan yang boleh diambil daripada keputusan eksperimen ini ialah empat cadangan algoritma tersebut mempunyai kecekapan yang lebih tinggi berbanding dengan IVFSS-FDM untuk membuat keputusan, dan empat pendekatan tersebut mempunyai kekuatan dan kelemahan masing-masing. Oleh itu, kaedah yang dicadangkan ini boleh digunakan untuk situasi yang berbeza.

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LIST OF ABBREVIATIONS

ASPR	Approximate Standard Parameter Reduction
AUDs	Australia Universities Dataset
BMPD	Blackberry Mobile Phone Dataset
DSS	Decision Support Systems
FSHKLDs	Five Star Hotel of Kuala Lumpur Dataset
IRDCCPR	Invariable Rank of Decision Choice Considered Parameter Reduction
IVFSS	Interval-Valued Fuzzy Soft Set
IVFSS-FDM	Interval-Valued Fuzzy Soft Sets based Fuzzy Decision Making algorithm
LUEDs	Lanzhou's Universities Evaluation Dataset
NENPR	a New Efficient Normal Parameter Reduction algorithm
NPR	Normal Parameter Reduction
OCCPR	Optimal Choice Considered Parameter Reduction
SASD	Students Anxiety Survey Dataset
SLD	Shenzhou Laptop Dataset
SPR	Standard Parameter Reduction

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Decision making is usually defined as a mental process, which involves judging multiple options or alternatives, in order to select one, so as to best fulfill the aims or goals of the decision maker (Power, 2002, French, 1986). Therefore, there are two main components involved in decision making: the set of alternatives, judged by the decision maker, and the goals to be satisfied with the choice of one alternative. The output of this process can be an action or an opinion of choice.

In general, decision making takes some time and effort until the choice is made, involving several activities, such as (Skinner, 2009, Clemen, 1996): identification of the decision problem, collecting and verifying relevant information, identifying decision alternatives, anticipating the consequences of decisions, making the decision, informing concerned people and public of the decision and rationale, implementing the selected alternative, evaluating the consequences of the decision.

The key step of this process is making the decision itself, i.e. choosing the most preferred alternative using judgment based on available information. However, decision making often occurs in the face of uncertainty (Marko, 2009). In other words, many practical and complicated decision making problems in environment, medical science, economics, engineering and social science involve uncertain, fuzzy, not clearly defined data. There are a wide variety of theories as diverse as probability theory, fuzzy sets (Zadeh, 1965), rough sets (Pawlak, 1982), and intuitionistic fuzzy sets (Atanassov, 1986) which can be considered as mathematical tools for modeling vagueness. But all these theories have their inherent difficulties as pointed out in (Molodtsov, 1999). Consequently, a Russian mathematician D. Molodtsov initiated the concept of soft set theory as a new mathematical tool for dealing with uncertainties in 1999. A soft set is parameterized family of the subsets of a universal set. It can be said that soft sets are neighborhood systems, and that they are a special case of context-dependent fuzzy sets. In contrast to all these theories, soft set theory is free from these difficulties and has no problem of setting the membership function, which makes it very convenient and easy to apply into decision making.

Presently, soft set theory has attracted attention of many researchers all over the world, who have contributed essentially to its development and applications. Theoretic study on the soft set is progressing rapidly. Some definitions of the new related operations on soft sets are firstly introduced. Furthermore, the soft set model can also be combined with other mathematical models. Therefore the definitions of soft groups, soft ideals and idealistic soft BCK/BCI-algebras, soft semirings, soft subsemirings, soft ideals and idealistic soft semirings, vague soft set, soft matrices have been given. It could be shown that soft set theory is closely associated with rough sets in (Pei et al., 2005, Herawan et al., 2009a). Soft sets can also be extended to fuzzy soft sets, intuitionistic fuzzy soft sets, interval-valued fuzzy soft set and interval-valued intuitionistic fuzzy soft set. As for practical applications of soft set theory and its extended models, great progress has been achieved. Data analysis approaches and data filling approach of soft sets under incomplete information are considered. Soft set theory can also be applied into data mining. An alternative approach for mining regular association rules and maximal association rules from transactional dataset using soft set theory is presented. The choice of convenient parameterization strategies such as real numbers, functions, and mappings makes soft set theory very convenient and practicable for decision making applications. This has motivated some researchers to use soft set theory for classification of the textures. A combined forecasting approach based on fuzzy soft sets was also proposed.

Applications of soft sets and its extended models in decision making is one of the most important practical applications of them. Maji et al. (2002) firstly showed an application of soft sets in decision making. Based on fuzzy soft sets, a novel method of object recognition (Maji et al., 2007) from an imprecise multi-observer data to deal with decision making is presented. Feng et al. (2010) showed an adjustable approach to fuzzy soft set based decision making by means of level soft sets. It is worthwhile to mention that some effort has been done to such issues concerning reduction of soft sets in the decision making problems. It was pointed out that the conclusion of soft set reduction offered in (Maji et al., 2002) was incorrect, and then a new notion of parameterization reduction in soft sets is presented in comparison with the definition to the related concept of attributes reduction in rough set theory. The concept of standard parameter reduction was introduced in (Kong et al., 2008), which overcomes the problem of suboptimal choice and added parameter set of soft sets. An algorithm for standard parameter reduction was also presented.

1.2 PROBLEM STATEMENT

Decision making can be regarded as an outcome of mental processes which are basically cognitive in nature leading to the selection of a course of action among several alternative. Every decision making process produce a final choice. The output can be an action or an opinion of choice. Decision making is vital for all categories of problems, which may be either long-range or short-range in nature (Chaundhuri et al., 2009). Many kinds of decision making are discussed in the literatures (Milan, 1982, Svenson, 1979, Beroggi et al., 1997, Delgado et al., 1998, Kevin et al., 2005, Kou et al., 2011, Gianluca, 2011, Busemeyer et al., 2009, Lin et al., 2008, Choong et al., 2008,). Decision Support Systems (DSS) are tools that an organization uses to support and enhance decision making activities (Bhatt et al., 2002).

However, the inherent feature revolving all decision making problems is the vagueness or uncertainty aspects (Leonardo et al., 1989, Czogała et al., 1986). In order to tackle this problem, a wide variety of theories as diverse as probability theory (Charles, 1970), fuzzy sets (Janusz, 1986, Lee, 1996), rough sets (Pawlak et al., 1994), intuitionistic fuzzy sets (Li, 2005, Liu et al., 2007, Lin et al., 2007), and interval-valued fuzzy sets (Dziech, et al., 1987) which can be considered as mathematical tools for modeling vagueness are applied into decision making. But all these theories have their inherent difficulties as pointed out in (Molodtsov, 1999). Consequently, a Russian mathematician D. Molodtsov initiated the concept of soft set theory as a new mathematical tool for dealing with uncertainties in 1999. In contrast to all these theories, soft set theory is free from these difficulties and has no problem of setting the membership function, which makes it and its extended models very convenient and easy to apply into decision making (Maji et al., 2002, Roy et al., 2005, Kong et al., 2009, Feng et al., 2010, Yang et al., 2009, Jiang et al., 2010, Qin et al., 2011a).

This thesis focuses on application of soft sets and its extended model for decision making, particularly, parameter reduction of soft sets and the related extended model for decision making. A parameter reduction is a minimum subset of parameters that provides the same descriptive or decision ability as the entire set of parameters. In other words, parameters in a parameter reduction are jointly sufficient and individually necessary. With the increase of data quantity, parameter reduction is very significant for application of soft set models in decision making.

Maji et al. (2002) firstly presented an application of soft sets that, in combination with rough sets, addressed a decision-making problem. The problem is displayed in the form of an information table and the reduction of the knowledge representation system in rough set theory to define the reduct-soft-set of a soft set is employed. The reduction of parameter sets in soft set theory and attributes reduction in rough set theory are in some ways similar to the approach of finding minimal parameters sets or attributes sets in decision-making but they use different methods. In rough set theory, firstly, they define single dispensable attribute while in soft set theory a single dispensable parameter cannot be defined as the dispensable attribute. Secondly, in rough set theory the attributes reduction is designed to keep the classification ability of conditional attributes relative to the decision attributes. There is not straightforward connection between the conditional attributes and the decision attributes. But for the soft set, the connection between the decision values and the conditional parameters are straightforward, i.e., the decision values are computed by the conditional parameters, and the reduction of parameters is designed to offer minimal subset of the conditional parameters set to keep the optimal choice objects. Thus the reduction of parameter sets in soft set theory and the reduction of attributes in rough set theory are different tools for different purposes. In general, one cannot be applied in the place of the other, which is pointed out by Chen et al. (2005). And then Chen et al. (2005) give a new definition of parameterization reduction of soft sets. Nevertheless, this approach only considers the optimal choice; the suboptimal choice is not referred. Moreover, the added parameter set is not taken into account too. In order to overcome the above problems, a new definition of normal parameter reduction (Kong et al., 2008) is proposed and a heuristic algorithm is presented to make normal parameter reduction. Two definitions of decision partition, based on the choice value and parameter important degree, are also introduced to analyze the algorithm. However, in reviewing this algorithm of normal parameter reduction, this thesis points out their drawbacks: the algorithm involves a great amount of computation and is surely time-consuming due to the complexity of decision partition and parameter important degree, that is of primary importance for the algorithm. Decision partition is interpreted as a partition of objects which partitions and ranks the objects according to the decision values based on the indiscernibility relation. Parameter important degree is defined based on decision partition. Therefore, based on this problem, there is a need for improving those techniques and developing a new efficient normal parameter reduction algorithm of soft sets having the ability to achieve lower computation complexity.

It should be noticed that the related membership degree are extremely individual and thus cannot be lightly confirmed in many fuzzy decision making applications. It is more reasonable to give an interval-valued data to describe degree of membership. Consequently, Yang et al. (2009) defined the concept of the interval-valued fuzzy soft set (IVFSS) by combing soft set with interval-valued fuzzy set. It is still a special case of a soft set. They also proved some of their basic properties and gave an algorithm to solve decision making problems based on IVFSS. However, up to present, few documents have focused on parameter reduction of IVFSS, which is very significant for application of this hybrid model in decision making. Accordingly, based on this problem, there is a need for giving definitions and heuristic algorithms of parameter reduction for the interval-valued fuzzy soft sets.

1.3 RESEARCH OBJECTIVES

This research embarks on the following objectives:

i. To propose new definitions of parameter reduction for the interval-valued fuzzy soft sets.
ii. To develop a new efficient normal parameter reduction algorithm of soft sets having the ability to achieve higher understandability and lower computation complexity.
iii. To develop related heuristic algorithms to achieve parameter reduction of the interval-valued fuzzy soft sets.

iv. To validate the proposed algorithms and to make a comparison between the proposed algorithms with the baseline techniques based on understandability and computation complexity on the real-life datasets and synthetically generated datasets.

1.4 RESEARCH OUTCOMES

The following are the research outcomes:

i. A new efficient normal parameter reduction algorithm of soft sets having the ability to achieve higher understandability and lower computation complexity.
ii. A proposal of four new definitions of parameter reduction of the interval-valued fuzzy soft sets: optimal choice considered parameter reduction, Invariable rank of decision choice considered parameter reduction, standard parameter reduction and approximate standard parameter reduction.
iii. Four validated algorithms for achieving optimal choice considered parameter reduction, Invariable rank of decision choice considered parameter reduction, standard parameter reduction and approximate standard parameter reduction for decision making.

1.5 RESEARCH SCOPE

The scope of this research falls within parameter reduction of soft set and interval-valued fuzzy soft set in decision making.

1.6 THESIS OUTLINE

The rest of this thesis is organized as follows:

Chapter 2: This chapter describes the decision making and uncertainty in decision making, recalls the fundamental concepts of soft set theory and the related extended models, reviews the existing researches that are related to applications on decision making using soft set theory and its extended models, introduce the previous works on parameter reduction of soft sets and its extended models in decision making.

Chapter 3: This chapter gives some new related definitions and proves theorems of normal parameter reduction. It describes a new efficient normal parameter reduction algorithm of soft sets that is proposed based on the oriented-parameter sum, which can be carried out without parameter important degree and decision partition.

Chapter 4: This chapter introduces four different definitions of parameter reduction in interval-valued fuzzy soft sets to satisfy decision makers' different needs. They are termed as optimal choice considered parameter reduction, Invariable rank of decision choice considered parameter reduction, standard parameter reduction and approximate standard parameter reduction. In addition, four according heuristic algorithms of parameter reduction are proposed, which are illustrated by examples. The four algorithms are compared and summarized.

Chapter 5: The chapter presents the comparison result between the proposed algorithm and the algorithm proposed by Kong et al. on three real-life datasets and ten synthetically generated datasets. The chapter also gives experimentations about four algorithms of parameter reduction of interval-valued fuzzy soft sets on three real-life datasets and ten synthetically generated.

Chapter 6: This chapter makes some conclusions and depicts future work for this research.